



Centre for Globalisation Research
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Estimating employer labour-market power and its wage effects*

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Abstract

The subdued wage growth observed over the last years in many countries has spurred renewed interest in monopsony views of the labour market. This paper is the first to measure the extent and robustness of employer labour-market power and its wage implications exploiting comprehensive matched employer-employee data. We find average (employment-weighted) Herfindhal indices of 800 to 1,100; and that less than 9% of workers are exposed to concentration levels thought to raise market power concerns. However, these figures can increase significantly with different methodological choices. Finally, when holding worker composition constant and instrumenting concentration, wages are found to be negatively affected by employer concentration, with elasticities of between -1.5% and -3%.

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1 Introduction

The limited wage growth observed in many countries in the recovery following the 2008 financial crisis has prompted important questions about the degree of wage setting power enjoyed by employers. These questions have gathered additional momentum with the complementary evidence that has emerged over the last decade on declining labour shares, the rise of 'superstar firms' (Autor et al. 2017), the relevance of 'no poaching agreements' in employment contracts (Krueger & Ashenfelter 2018), and the limited disemployment effects of minimum wages. While these findings may still be reconciled with largely competitive labour markets, the relevance of evidence on employer labour-market power is clear.

This paper contributes to the literature on monopsony (Staiger et al. 2010, Manning 2010, 2011, Falch 2010, Matsudaira 2014, Card et al. 2018) by addressing two major questions: 1) how concentrated are local labour markets? and 2) what is the impact of concentration on wages? We are the first to address these questions by exploiting rich matched employer-employee data. Our data covers the full population of workers (and occupations) in a country, Portugal, including not only manufacturing but also services as well as both incumbent workers and new hires. Furthermore, in contrast to other papers in this literature, our data also includes information on the occupation and region and wages of each worker. All these variables are particularly detailed and comparable not only across firms but also over time, during the 23-year period that we cover.

These two data dimensions - coverage of all occupations and of the entire labour market - are critical for a comprehensive analysis of employer market power. The majority of workers in developed countries have been for many decades employed in the services sector (which is however not covered in a number of data sets used in this research) and concentration levels may be much higher in manufacturing than services. Moreover, a less than comprehensive knowledge of the spread of comparable occupations across firms as well as an analysis based exclusively on employment flows or stocks may also lead to overestimated measures of concentration.

A key reference in this literature is Azar et al. (2017) (see also Azar et al. (2018)): using data on the top occupations from a leading U.S. employment website, they find that the average labour market is highly concentrated. Moreover, using a subset of their data for which posted wage information is available, they find that concentration is associated with

large declines in earnings: cuts of 17% from moving from the 25th to the 75th percentile of the Herfindhal distribution.¹

Our results are consistent with the previous literature in that we also find that employer market power is a significant phenomenon. However, our results indicate that its magnitude is smaller than in previous evidence that could not draw on the same type of data. This finding applies both in terms of the percentage of the workforce employed in high-concentration local labour markets and in terms of the size of the wage effects of concentration. Specifically, we find that less than 9% of workers are exposed to concentration levels thought to raise market power concerns (DoJ/FTC 2010). However, we also show that these measures can more than double with different methodological choices, in particular when considering more detailed occupation codes and less aggregated geographical areas.

Our wage analysis highlights the relevance of controlling for worker (and firm) composition. When not doing so, we find a positive association between employer concentration and wages. This reflects the fact that concentrated labour markets tend to be characterised by large firms, which will tend to be more productive and enjoy higher product market power. These two dimensions will in turn create scope both for selection in hirings (employing workers of higher productivity) as well as rent sharing, through bilateral bargaining, particularly when labour market policies are more supportive of collective bargaining.

We address these factors by again exploiting the richness of our data and estimating the relationship between wages and concentration using both worker and firm fixed effects. We follow closely Azar et al. (2017) and employ instrumental variables based on the number of firms in the same occupations but other local labour markets. In these models, we find a negative effect of local labour market concentration on wages, with elasticities of between -1.5% and 3%. These results indicate that workers that would move from low- to high-concentration local labour markets (percentiles 25th and 75th, respectively) would experience a drop in wages of approximately 3.5%, significantly smaller than in Azar et al. (2017). This smaller effect may reflect the role of labour market institutions, in particular collective bargaining, which is much stronger in Portugal than the U.S, and can lead to rent sharing, thus eroding the negative effect of employer market power.

¹See also Benmelech et al. (2018) and Rinz (2018) for two recent contributions focusing on the case of the U.S and Duan & Martins (2018) who also examine the role of employer labour market power in shaping rent sharing in China. The last two papers examine the manufacturing sector only. The three papers examine data that does not provide information on occupations per firm.

The structure of the remaining of the paper is as follows: Section 2 presents the data used. Sections 3 and 4 describe our main measures of employer concentration and a comprehensive sensitivity analysis that we also conduct. The wage effects results are presented in Section 5. Finally, Section 6 concludes.

2 Data

Our empirical study is based on the ‘Quadros de Pessoal’ (Personnel Records) data set, a comprehensive matched employer-employee panel. This data set provides detailed annual information on all firms based in Portugal that employ at least one worker and on all their employees, including time-invariant firm and person identifiers. The data set corresponds to an annual mandatory survey collected by the Ministry of Employment for the purposes of monitoring and enforcing compliance with employment law.

Worker information concerns the month of October of each year and features a number of variables, on an individual basis, the most important for us being the wage (base and total) and the occupation. The latter is defined using the national occupations classification, which features about 1,400 different entries, defined at a six-digit level (the national occupation classification, unchanged between 1995 and 2009). Other worker-level variables that we also consider include the year and month of birth, the year and month of hiring in the firm, the collective agreement applicable, and the job title code of the worker under the collective agreement. At the firm-level, we use the geographical location of the firm (at the ‘concelho’ level - over 450 different locations - and the more aggregated ‘distrito’ level - 30 different locations, including the islands in Azores and Madeira).²

Our benchmark definition of local labour markets is based on the occupation definition composed of 1,400 entry and the region definition composed of 30 entries (‘distritos’). These regions have an average size of about 3,000 square kilometres and 340,000 inhabitants, including multiple cities and villages in most cases. 18 regions are located in the continental part of Portugal; the remaining 12 correspond to the islands of the Azores and Madeira archipelagos. With the exception of some areas in the least populated and least densely populated regions, typically located in the East and South of the country, all urban or industrial areas

²We use all worker observations in the data set except those with missing information on the occupation, date of hiring, and region variables. Other worker-level variables available are gender, schooling, hours of work, and type of employment contract. At the firm-level, the data also provides information on industry (five-digit variable), total sales, legal type of firm, capital equity, and type of ownership.

can be reached from virtually all residential areas in each district in less than one hour by car and in many cases in less than one hour by public transport as well. With the exception of the district of the capital city, Lisbon, the largest city in each region is located closed to the geographical centre of the region. This ensures limited overlap between commuting zones of neighbouring regions. This benchmark definition also leads to an average of 14,500 local labour markets (occupation-region pairs) per year over the 22-year period covered, as we discuss below. In our analysis, we consider the years between 1991 and 2013 (except 2001 which is not available). In a number of regression analyses, we focus on the subperiod of 1991-2006 as our worker identifier suffers from a discontinuity between 2006 and 2007.

3 Employer concentration

Following the literature, we measure employer concentration using the Herfindhal-Hirschman index (HHI):

$$HHI_{l(o,d),t} = \sum_{j=1}^{N(l,t)} share_{j,t}^2, \quad (1)$$

in which $HHI_{l(o,d),t}$ is the HHI measure for local labour market l (correspond to both occupation o and district d), in in year t ; $N(l,t)$ is the number of firms employing (or having hired) workers in that occupation, district and year; and $share_j$ is 100 times the ratio between the employment (or new hires) of firm i in year t and the total employment (or new hires) in the local labour market of that firm (occupation o and district t in year t). Given this definition, the HHI can range between 0 - no concentration - and 10,000 - maximum concentration.

In Table 1, we present the HHI indices for each year, considering both the cases of employment and of new hires (defined here as workers employed as of the census month - October of each year in almost all cases - and hired over the previous 12 months). The results indicate that the HHIs in the case of stocks range between 720 and 900, while in the case of flows they range between 700 and 1,150. These figures are significantly below the concentration levels thought to raise market power concerns, at least in the case of product markets, at HHIs of 2,500.³

³Figure A1 presents an illustration of this approach, focusing on one particular occupation, construction and public works technician (code 31120), in a particular district (Leiria), and in a particular year (2006). Each observation in the histogram corresponds to one of 240 firms located in the district that employ at least one worker with this occupation in that year. The Herfindhal index for this observation is 52.7, highlighting the significantly dispersed nature of employment of this occupation in this district, as over 200 of the 240 firms employ only one worker in this occupation.

As can be seen from Figure 1, which presents graphically the HHI time series, there is no particular trend that can be discerned from our results, for instance in terms of an increase in labour market concentration over time. If anything, we find some suggestive downward trend, particularly over the period 1998-2010, in the employment stocks measure. The data may also be consistent with moderate countercyclicality, particularly in the hirings measure: years such as 2004, 2009 and 2012, when unemployment increased significantly, are also periods of above-average HHIs. These high HHIs will reflect not only the steep reductions in hirings during downturns - which are known to be common in such periods - but also the particular distribution of hirings across firms that arises then, in such a way that the HHI concentration measure increases significantly.

Furthermore, we find from comparing the stock and flow series - Table 1 - that except for the first two years, the HHIs in stocks are always higher than the corresponding (same year) HHI's in flows. For instance, in 2006, the former is 777 and the latter 1030. Overall, flows HHIs are, on average, 30% higher than stocks HHIs. This gap reflects the fact that now all firms employing workers in a give year also hire in that year.

Table 1 also presents information about the number of occupation-district cells used to compute the HHIs as well as the total number of workers and hirings in that year. The first series ranges between 10,000 and 20,000 cells, reflecting the growth of the formal sector since the early 1990s and then a change in occupation codes in 2010, as well as the labour market effects of the financial crisis and debt crises from 2008. The numbers of workers and new hires follow a similar pattern to that of local labour market cells, increasing from 1.9 million employees (320,000 new hires) to 3.3 million employees (760,000 new hires), over the period.

We also describe our data in terms of the nearly 320,000 pooled local labour market cells, over the entire period of our analysis, 1991-2013 - Table 2. The mean number of workers per cells is 8,387 (when weighting by employment) and 176 (when not), while the mean number of new hires is 1,760 (35). The mean HHI measures are, when considering employment stocks, 798 (weighted) and 4,205 (unweighted). When considering employment flows (new hirings), these figures are 1,055 and 3,311, respectively. The latter figure is the most comparable with those reported in Azar et al. (2017), based on 16 of the most frequent occupations posted on a large online jobs board in the US over the period 2010-2013, which present a remarkably similar mean HHI figure of 3,157. While (Azar et al. 2017) focus their analysis on average

HHIs across local labour markets, we focus on employment-weighted HHIs, i.e. we adopt the perspective of the average worker, to take into account the possibility that is supported in our analysis that concentrated labour markets tend to be characterised by small numbers of workers. We also find an interquartile range of 858 HHI points (950-92) when weighting cells by employment (6,638=7,551-913, when no weighting).⁴ We will consider these figures later, when computing the wage implications of more concentrated markets, together with the elasticities presented in Section 5.

To illustrate in greater detail our findings, the left- and right-hand-side histograms in Figure 2 present the distributions of HHIs across local labour markets (district-occupation pairs) in a particular year, 2006, not weighting or weighting the cell in terms of their employment, respectively. As in the case of the pooled cells, we find that this weighting makes a significant difference to the resulting distributions as the most concentrated local labour markets tend to be those employing fewer workers, in many cases a single worker. Very similar results emerge when considering different years than 2006. The range of HHI concentration levels between 0 and 200 is the one that applies to most workers, as in the case study of construction/public works technician in the district of Leiria presented above and in Figure A1.

To provide greater detail on our results, we also describe here a subset of occupations the highest and lowest HHI values. Focusing, as an illustration, on those occupations employing at least 1,000 workers in a particular year, 2006, the occupations that are associated to the lowest levels of concentration are 'Director and managers of small firms' (13110-13199 occupation codes; average HHI of about 30), 'Production director' (12220; 34), and 'Secretary' (41150; 39). These cases reflect the fact that almost all firms employ only one or at least one director and secretary. On the other hand, the occupations with the highest levels of concentration are 'Postman' (41420; 9,950), 'Train driver' (83110; 9,880), and 'Industrial robot operator' (81729; 9710). The first two cases reflect the fact that the post distribution and train transport industries are monopolies in Portugal, as in many other countries.

⁴Standard deviations of HHI measures range between around 1,800 (weighted analysis) and 3,700 (unweighted case), regardless of the type of measure (stock or flow). Furthermore, mean salaries range between 566 and 768 euros, depending on whether one is considering base or total wages and weighted or unweighted means.

4 Sensitivity analysis

The results above follow from choices we made regarding the definition of a local labour market. To investigate the robustness of our findings, in particular the generally low levels of employer labour-market concentration, we exploit the richness of our data set to measure local labour markets in up to five alternative ways. In all cases, we depart from our benchmark model described above (based on 1,400 occupations and 30 districts) and introduce changes in these or other parameters of the analysis. All modifications are deliberately selected so that they are likely to increase concentration measures. In this way, we can better understand what may be the upper bounds of these measures.

In the first alternative approach, we restrict the time window under which a worker is considered a new hiring, from the 12-month period used before to six months only. Our interest in this analysis stems from the vacancy perspective adopted in other papers (Azar et al. 2017, 2018). Table 3, second row, presents the results (the first row presents the benchmark results, weighted by employment, to facilitate the comparison with alternative measurement approaches). We find that the HHI for new hirings increases by 17%, from 1,007 to 1,170 but the employment stocks results are left unchanged. The number of cells is also reduced, as one would expect, as in some cases all local labour market hirings take place in the first half of the year. Specifically, the number of cells falls from over five million to 3.34 million. Overall, despite halving the time window adopted for the consideration of new hires, the degree of concentration does not increase by a similar magnitude. More important, the average HHI is still significantly below the 2,500 threshold at which concentration has been thought to have an impact on market outcomes; and the percentage of workers in this case only (new hirings) that are subject to HHIs above 2,500 is below 13% (compared to 8.7% in the benchmark case).

A second alternative measure involves the consideration of collective bargaining job titles instead of occupations. Collective bargaining plays an important role in the labour market of Portugal and many other European countries, in some cases because of workers affiliation rates, in because of the widespread use of extensions (Martins 2014). These extensions, issued by the government, determine that the collective agreements need to be followed by virtually all firms and employees in the relevant industry, even those not members of the trade unions or employer associations that conducted the bargaining. In this context, the over 30,000

job titles established in collective agreements (each one of which subject to its time-varying minimum wage) can be interesting alternatives for the classification of workers in terms of their occupations, especially as they are also registered in the 'Quadros de Pessoal' data set that we use. However, these alternative occupation measures are also very likely to overestimate the number of local labour markets and therefore led to spuriously high concentration figures. For instance, a secretary in the metalwork industry will have a different job title code than a secretary in the retail sector even if they are located in the same district. In other words, the relevance of this measurement approach will depend on the degree of industry-specific skills or differentiation in individual occupations.

Under this second definition of occupations, we find that the number of labour market cells increases dramatically, from 14,466 to 79,088, which reflects the fact that the occupation codes also increase by a factor or more than 20 as we move from the benchmark case to the collective bargaining job titles.⁵ More importantly, we find that our average HHI measures more than double in both cases (employment stocks and flows), reaching 1,780 and 2,011, respectively. The percentage of workers in local labour markets with HHIs above the potentially critical thresholds of 2,500 also more than doubles, reaching nearly 20%, a figure similar to the one found for the U.S. in Azar et al. (2018). Given the potential double-counting of occupations in this approach as described above, we regard this alternative measure as an upper bound of concentration.

Our third alternative change from our benchmark measure is based on considering more disaggregated regional definitions ('concelhos' instead of 'distritos'). This option is influenced by the findings in Manning & Petrongolo (2017), which present evidence that labour markets can be very local, as jobseekers reduce their search efforts considerably at longer distances. In our case, the 'concelho' level has 15 times more units in total when compared to 'distritos' and are roughly equivalent to U.S. counties. As this level will be too small to be considered a distinctive commuting zone in the two largest metropolitan areas, Lisbon and Porto, which are served by good public transport links, we still consider units based on 'distritos' (not 'concelhos') in those two cases. We find, first, that the the number of occupation-region-year cells increases by more than four times from the benchmark case to nearly 60,000, reflecting the far more disaggregated nature of the local labour market - Table 3, fourth row. On the

⁵The average number of workers and hirings also increases reflecting the fact that the number of missing observations in collective bargaining titles is more limited than under the occupations variable used before.

other hand, the HHI measurements also increase, to 1,477 and 1,882, for employment stocks and flows, respectively. While this change is significant, these averages fall short of the levels measured in the case of collective bargaining titles and also correspond to a smaller percentage of workers in local labour markets above the critical thresholds of 2,500 (17.7% in this case).

Next we examine the role of the large percentage of small firms in the labour market of Portugal as potential driver of the main results above, namely the low HHI levels found so far. As documented in Cabral & Mata (2003) and Braguinsky et al. (2011), Portugal tends to exhibit a different distribution of firm sizes than the average of other developed countries, with a larger mass at smaller sizes. A phenomenon also observed in other (Southern) European countries, this large percentage of small firms may be explained by a number of factors, including restricted access to credit, lower management quality, regulations/tax compliance issues (making firms unwilling to grow too much to more easily not be subject to such constraints), and employment law strictness (prompting firms to make greater use of service providers/independent workers instead of formal employees to have greater flexibility in hiring and firing (Martins 2009b)). Regardless of the relative importance of the factors above, the prevalence of small firms, while potentially negative in terms of productivity and therefore wages, may also potentially affect the comparability of our measurement of market power in the labour market, by downplaying the role of larger firms in each local labour market.

We examine the issues above by removing from our analysis any firm that employs fewer than ten employees in a given year. Table 3, second row from the end, indicates that, as expected, this restriction leads to a significant decrease of the average number of workers and hirings, to 1.89m and 0.38m, respectively. Moreover, the HHI measurements increase significantly, by more than 40%, both in the cases of employment stocks and flows, to 1,124 and 1,426, respectively, but not as much as in other measurement approaches. This is also reflected in the fact that the percentage of workers under HHI levels above 2,500 in this case is the second lowest across the different approaches in this subsection, at 12.5%. We therefore find that, while the small firm dimension influences, as expected, our result on concentration, it is not a critical factor behind the relatively low concentration measures found in our benchmarking analysis.

Finally, we consider the sectoral dimension. As indicated before, some studies of employer concentration can only examine the manufacturing sector only because of data constraints

(Benmelech et al. 2018, Rinz 2018, Duan & Martins 2018). In order to shed light on the potential impact of such methodological approach, we restrict our attention to manufacturing sector firms only. The last row of Table 3 presents the results, which indicate significantly higher levels of concentration, with HHI's of 1,190 and 1,683 (employment stocks and flows, respectively) and an employment share above 2,500 of 13.7%.⁶

In conclusion, by exploiting the richness of our matched employer-employee data, covering the universe of firms and their employees, we find that the measurement of employer concentration is sensitive to different methodological choices. This sensitivity refers to different concepts used when defining not only the occupational and regional dimensions, but also the focus on employment stocks or flows and the potential inclusion or exclusion of smaller firms or particular sectors.

In this Section, all departures from the benchmark case entailed increases in concentration by construction. Other types of changes that could be considered would move the results in the opposite direction. Examples would include more aggregated occupation classifications (four- or three-digit level, instead of the five-digit level considered) or longer time windows in the measurement of hirings. Of course, one could also consider measurement approaches that would combine some or all of the changes examined here, in particular the first three.⁷ All in all, our range of estimates presented here offer a better understanding of the sensitivity of concentration measures to different methodologies.

5 Wage effects

It is well known that, if workers have limited choice in terms of alternative employers in their occupation and commuting zone, firms may exploit the resulting wage setting power by reducing the pay levels offered to and eventually accepted by workers. We argue here that, alternatively, high levels of employer concentration, in particular when involving large firms, may lead to the emergence or strengthening of unionisation and collective bargaining.

In the same way that workers faced with a dominant employer in their local labour market

⁶All these measures also hold when considering a constant set of (7,968) local labour markets that are present in all years over the 1995-2009 period and our benchmark parameters. However, concentration drops even further, by approximately 15% across all years and types of measurement (stocks or flows) - results available upon request.

⁷A joint focus on hirings (in particular over a six-month period), defining occupations in terms of collective bargaining titles, and considering regional markets based on less aggregate measures ('concelhos') would certainly lead to a much HHI level and a much higher percentage of workers in local labour markets with a HHI above 2,500.

will not have many alternatives, a dominant employer faced with a powerful union may have to share at least some of its rents with its workers, particularly when the firms have not only labour market power but also rent-generating product market power. The countervailing, union-based mechanism would lead to a more balanced relationship between the employer and the employee sides, where the wage setting power is attenuated and the rent sharing dimension may even possibly gain greater predominance.⁸ Local labour markets may also be associated to industrial clusters, generating external scale economies, leading to higher wages (see (Figueiredo et al. 2014), which also uses the same data set as in this paper).

In this context, after establishing the levels of employer concentration across labour markets in the previous Section, we now estimate the impact of such concentration on workers' wages. More specifically, in our benchmark local-labour-market specifications, we estimate the following equation:

$$\log Y_{i,l(o,d),t} = \alpha + \beta \log HHI_{l(o,d),t} + \delta_{l(o,d)} + \phi_t + \tau_i + \epsilon_{l(o,d),t}, \quad (2)$$

in which $Y_{i,l(o,d),t}$ is the (monthly) wage of worker i in local labour market $l(o,d)$, of occupation o and district d , in year t ; and $HHI_{l(o,d),t}$ is the Herfindhal-Hirschman index of the same local labour market $l(o,d)$ in year t . $\delta_{l(o,d)}$ are fixed effects for each local labour market, ϕ_t are fixed effects for each year, and τ_i are worker fixed effects. Given our log-log specification, the estimate of β indicates the elasticity of the individual wage with respect to the Herfindhal index of the market where the worker is based in each year.⁹

Table 4 presents the first set of results, covering the full 1991-2013 period. We consider three specifications: the first controlling only for year fixed effects, the second controlling as well for occupation fixed effects and district fixed effects, and the third controlling instead for local labour market fixed effects (occupation-district pairs). In all cases we exclude worker fixed effects to obtain estimates equivalent to those derived from pooled worker data. We find

⁸See Martins (2009a) and Card et al. (2018) for evidence of rent sharing in Portugal, based on the same data set used here. As discussed before, collective bargaining is pervasive in Portugal, despite low unionisation rates, given the nearly automatic extension of collective agreements. Collective agreements tend to cover the entire country, therefore reducing the scope for differentiated adjustments at different regions. As to other labour market institutions that may also affect wage determination, the most important may be minimum wages and unemployment benefits. While the former were relatively low in Portugal during the period under analysis (particularly until 2006), unemployment benefits were relatively generous, in terms of replacement rates and maximum duration potential.

⁹Unlike in Azar et al. (2017), we do not consider specifications that control for local labour market tightness as we do not have information on applications for each vacancy.

in all three specifications significantly positive elasticities, with coefficients ranging between 0.018 and 0.045. These results are at odds with the view that employer concentration erodes wages but are consistent with the perspective that employer concentration can be a proxy for rent sharing through (collective) bargaining.

We find similar positive effects when controlling for worker fixed effects and analysing the period 1991-2006 - see Table 5.¹⁰ However, the magnitude of the coefficients drops considerably, now ranging between 0.004 and 0.012 across the three specifications. These results suggest that high-wage workers tend to be employed in high-concentration local labour markets and that rent sharing can be relevant in shaping the wage distribution.

In contrast to the implicit assumption in the previous analyses, one may argue that concentration measures are not likely to be exogenous with respect to wages. Larger local labour markets (with lower concentration levels) may attract more productive firms that pay higher wages and want to be able to hire workers more quickly, for instance. While we control for time-invariant differences across local labour markets and for economy-wide year effects, our results could be influenced by labour demand or labour supply shocks at the level of the local labour market. An increase in the number of university graduates in particular occupations may lead to lower levels of concentration and lower wages in the resulting jobs. Declines in the international demand for specific products may lead to both lower labour demand and lower wages (Cabral et al. 2018) as well as possibly more concentrated employment in specific occupations.

We address this issue by following Azar et al. (2017) and earlier research in industrial organisation and labour economics and develop an instrumental variable for $HHI_{l(o,d),t}$. This variable corresponds to the average of $\sum_e \log(1/N_e)/29$, where N_e indicates the number of firms in each one of the other (29) regions ('distritos'), except d , that employ workers of the same occupation o , in the same year t . This instrumental variable does not depend directly on market shares as it is based on the number of firms and not their employment. Moreover, it provides variation in local labour market concentration driven by changes across the country except for the specific local labour market that is being instrumented. In this way, we can obtain estimates that are not biased by the local labour demand or labour supply shocks

¹⁰In this and the following tables, we focus on the period 1991-2006, given the limitation with the worker identifiers described in Section 2. We also reestimate the models of Table 4 without worker fixed effects but considering the period 1991-2006 instead. The results are presented in Table A1 and are very similar to those obtained for the longer period.

mentioned above.

Table 6 presents our first set of IV results using the variable above. In the first stage regression, we find the positive (and highly significant) effects predicted. The higher the average number of firms employing workers of the same occupation in other regions, the lower the value of the instrument, and the lower the level of concentration in the local labour market. In the second stage, we find again significant positive effects but only when not controlling for local labour market fixed effects. In our specifications with such controls, either for occupations and districts separately (column 2) or for occupation-district pairs (column 3), we find negative effects, of -0.016 and -0.014, respectively.¹¹ Given the interquartile range of nearly 900 HHI points presented in Section 2 and its resulting difference in logs of 2.33 points, we estimate that workers that would move from low- to high-concentration local labour markets (defined here as percentiles 25th and 75th, respectively) would experience a drop in wages of approximately 3.5%.

We now conduct a number of robustness checks around our main results above. In the first case, we consider an alternative measure of employer concentration, the HHI based on employment flows (and not stocks as before). Given that this measure may be more directly linked to the specific situation in the labour market in each year, this may better reflect the opportunities for wage growth of incumbent workers for instance in terms of mobility to other firms. On the other hand, wages can be subject to downward nominal wage rigidity implying that even a difficult situation in the local labour market, with limited and highly concentrated new vacancies may not translate into significant wage cuts or significantly lower wage growth. The results, presented in Table 7, indicate that the two types of mechanisms with opposite effects described here appear to cancel out. The estimates are virtually equal, only marginally smaller, when compared to those obtained under the HHI measure obtained from employment stocks. An additional advantage of this equation is that it may be the closest to the benchmark results in Azar et al. (2017), which find much higher elasticities of between -0.116 and -0.2.

Our second robustness test involves the analysis of potential nonlinearities in these effects. For instance, the small wage effects that we have obtained so far may reflect the fact that most of our HHI distribution is at relatively low concentration levels. These wage effects may

¹¹The worker fixed effects approach plays a key role in this result. When running models without these fixed effects but instrumenting concentration, we again find positive effects on wages - Table A2.

be considerably higher at higher HHI levels. We approach this question by restricting our analysis to the top 25% of the HHI distribution in our sample. However, as presented in Table 8, we find again very similar elasticities, ranging between -0.014 and -0.018. Similar results also arise when using base instead of total wages as our dependent variable (Table A3) and when considering HHI measures based on collective bargaining job titles instead of our benchmark set of occupations (Table A4).

Finally, we examine the role of firms in wages and their potential confounding effect in studies of employer labour-market power. As discussed above, highly-concentrated labour markets may derive their concentration levels from the presence of large firms that will tend to have both higher productivity and stronger product market power. These competitive advantages may then be shared with workers via collective bargaining, for instance. In this last robustness check, we add firm fixed effects to our equation to control for the forces above. Identification of firm and worker effects will be based on mobility of workers across firms over time. While we are not able to separately identify region from firm effects, as firms are virtually always present in the same region over time, we can control for local labour market effects, as we have multiple firms and workers in each occupation-district pair.

Table 9 presents the results of this more comprehensive specification, in which we find elasticities of -0.028 and -0.033, which are twice or more than twice the ones obtained before in IV models with worker fixed effects. This increase in (the absolute value of) the elasticities is consistent with our discussion above that relatively high-wage firms tend to be more common in high-concentration local labour markets. Such correlation can introduce an upward bias in the wage-concentration elasticities that may make one underestimate the overall negative effect of concentration on wages. Given the same interquartile range presented above of 2.33 log points, these results indicate that workers that would move from low- to high-concentration local labour markets (defined here as percentiles 25th and 75th, respectively) would experience a drop in wages of approximately 7%.

6 Conclusions

Exploiting rich matched data for Portugal, we made a number of contributions to the literature on monopsony. In particular, we present evidence of the significance of employer labour-market concentration, in terms of its magnitude and wage effects. First, we find that at least

9% of workers can be regarded to be exposed to concentration levels thought to raise market power concerns, a percentage that has remained relatively stable over the 20-year period covered. Second, we estimate wage-concentration elasticities that are significantly negative, ranging between -1.5% and -3%, implying that workers that would move from between the bottom and top quartiles of the concentration distribution could see their wages fall by between 3% and 7%.

The latter result suggests that employer market power is an important but not necessarily major driver of wage inequality. The smaller elasticities that we document compared to the case of the U.S. may follow from the different labour market institutions in the two countries. In particular, sectoral collective bargaining in Portugal sets common industry wage floors across multiple regions, regardless of the specific conditions of the local labour market, including its concentration level. These practices are common in many other European countries but contrast to the case of the U.S.

From a methodological perspective, our findings highlight the sensitivity of concentration measures with respect to different parametric choices, including the sector under analysis, the focus on employment flows or stocks, and the level of aggregation of occupations and geographical areas. For instance, we find that concentration measures can more than double depending on the approach adopted. Given the relative novelty of measuring concentration in local labour markets, these estimates may also inform policy makers that wish to establish critical thresholds that may be more appropriate to address monopsony.

Finally, our results also underline the importance of taking into account both the worker and the firm heterogeneity dimensions when estimating wage-concentration elasticities. High-concentration labour markets may feature larger and more productive firms, which tend to pay higher wages and employ more skilled workers. As we show in our results, these factors can potentially obscure or bias downward any existing negative effects of concentration on wages when such sources of heterogeneity are not taken into account.

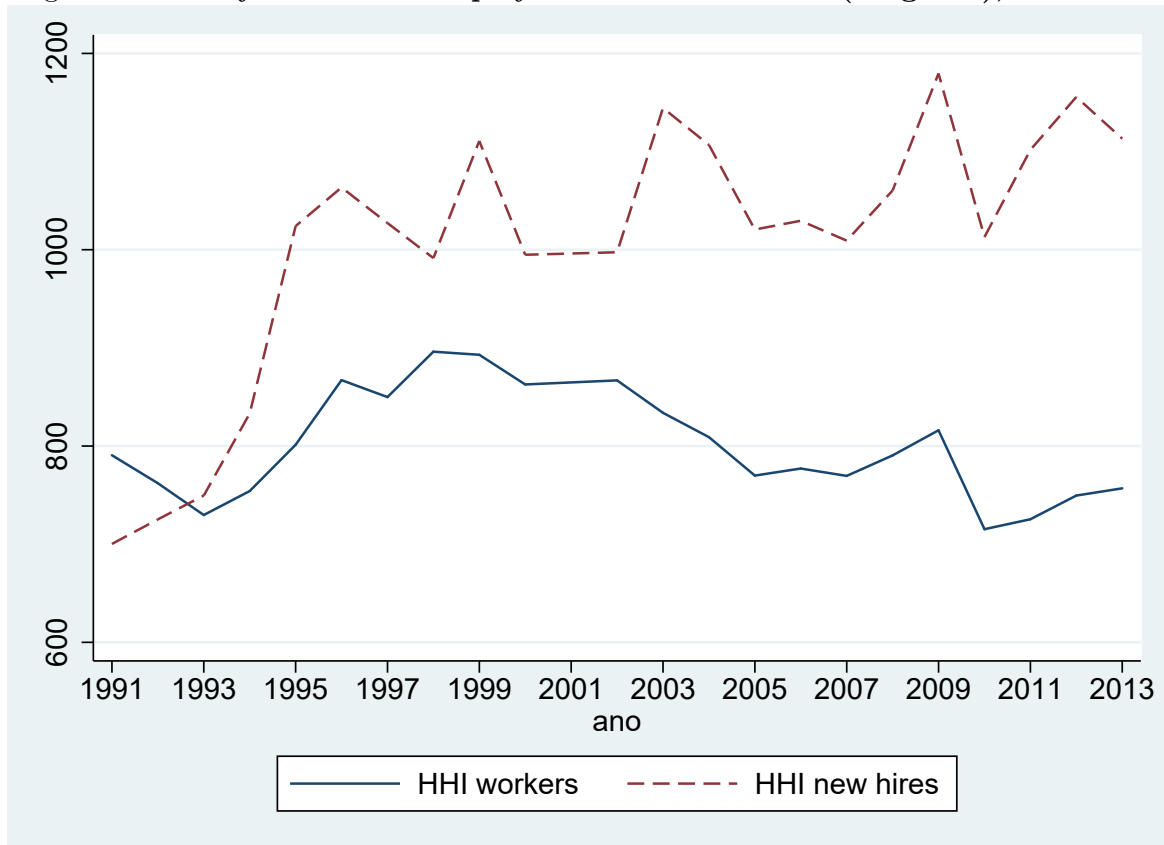
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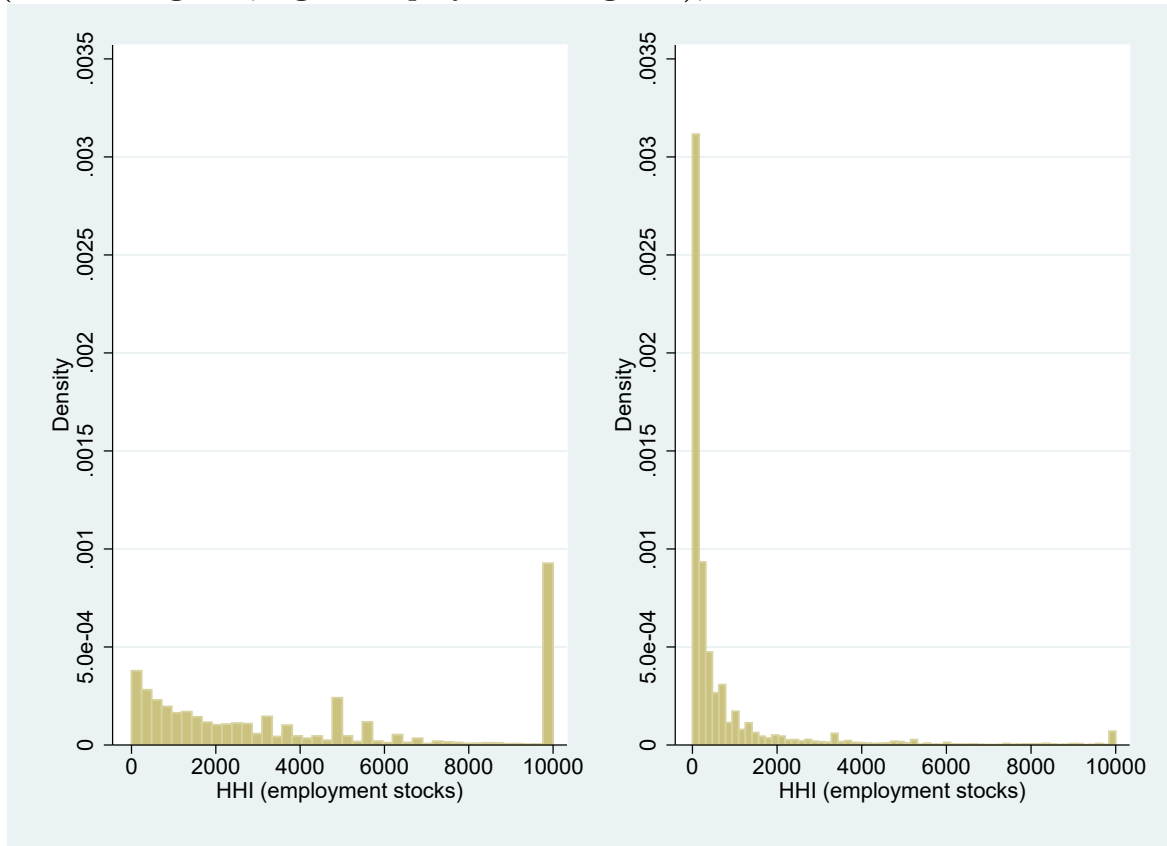
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Figure 1: **HHI by number of employees and of new hires (weighted), 1991-2013**



Notes: Own calculations based on the 'Quadros de Pessoal' data set. See the Herfindhal index formula in equation 1 and Table 1 for more details on each time series. Figures for 2001 are interpolated as worker-level data for this year is not available. Occupation codes change in 1995 and 2010. The weights of the two series are the employment count of each occupation-district-year cell. 'HHI works' corresponds to employment stocks; 'HHI new hires' corresponds to employment flows (workers employed in October of each year (March in 1991/93) and hired over the previous 12 months).

Figure 2: Distribution of HHI by number of employees across local labour markets (left: unweighted; right: employment-weighted), 2006



Notes: Own calculations based on the 'Quadros de Pessoal' data set. See the Herfindhal formula in equation 1. Left-hand-side distribution: All local labour markets (occupation-district pairs) carry the same weight, regardless of the number of workers. Right-hand-side distribution: Each local labour markets (occupation-district pairs) carries a weight in the histogram that is proportional to its employment level.

Table 1: **HHI values (weighted), 1991-2013**

Year	HHI (workers)	HHI (hirings)	N. cells	N. workers	N. hirings
1991	790.6	700.3	10237	1963350	398971
1992	762.2	725.3	10211	1986647	380778
1993	729.7	749.6	10352	1980966	349980
1994	754.2	833.2	10469	1927961	321426
1995	801.3	1024.1	12413	1993603	339957
1996	867.2	1063.4	12272	1968477	346704
1997	849.9	1027.2	12657	2150737	438352
1998	896.1	991.5	13717	2185320	454425
1999	893.0	1110.8	15066	2283315	449316
2000	862.7	994.9	15721	2494350	552783
2002	866.9	997.4	17556	2695196	584535
2003	833.9	1144.4	18595	2800003	540625
2004	809.1	1106.8	19178	2891959	569950
2005	769.9	1020.6	19640	3065839	630755
2006	777.1	1029.5	19770	3111190	661384
2007	769.6	1009.3	19963	3220102	742339
2008	790.5	1060.4	20107	3267603	763912
2009	816.1	1179.6	19985	3125383	623430
2010	715.3	1013.0	10149	2842842	561172
2011	725.4	1101.8	10119	2797408	525329
2012	749.6	1155.6	10057	2616314	423911
2013	756.9	1113.2	10023	2608058	476152

Notes: See the Herfindhal index formula in equation 1. HHI (workers) denotes the mean Herfindhal index in each year considering the distributions of employees across firms in each district-occupation-year cells. HHI (hirings) denotes the mean Herfindhal index in each year considering the distributions of new hires (workers hired over the previous 12 months, as of October of each year (March in 1991 up to 1993)), across firms in each district-occupation-year cells. 'N. cells' indicates the number of district-occupation pairs in each year. 'N. workers' ('N. hirings') indicates the total number of workers (hirings) in each year. Figures for 2000 are not presented as worker-level data for this year is not available. Occupation codes change in 1995 and 2010. The weights of the two series are the employment count of each occupation-district-year cell.

Table 2: **Descriptive statistics, district-occupation-year cells, 1991-2013**

Variable	Obs	Unweighted		Weighted		Min	Max
		Mean	Std. Dev.	Mean	Std. Dev.		
Year	318,257	2002.6	6.1	2003.0	6.5	1991.0	2013.0
Number of workers	318,257	175.9	1201.7	8386.7	17180.8	1.0	121286.0
Number of new hires	318,257	35.0	276.3	1759.7	3456.8	0.0	21924.0
HHI (n. of workers)	318,257	4204.7	3696.0	797.6	1746.7	1.0	10000.0
HHI (n. of new hires)	318,257	3311.1	3880.1	1055.0	1972.3	0.0	10000.0
Mean base pay	316,391	626.2	605.7	566.2	532.1	0.0	25837.7
Mean total pay	316,391	768.1	914.3	682.6	722.7	0.0	229576.9

Notes: Each observation corresponds to a district-occupation combination observed in a year. 'Unweighted' ('Weighted') denotes statistics in which all cells carry the same weight (each cell carries the weight proportional to its employment). 'Mean base pay' is the average nominal base pay of the workers employed in the district-occupation-year cell. 'HHI (n. of workers)' denotes the Herfindhal index for each district-occupation-year cell.

Table 3: **HHI mean values, different measurement approaches**

Measurement type	HHI		Average number of			% workers HHI \geq 2,500
	Workers	Hirings	cells	workers	hirings	
Benchmark case	799.4	1006.9	14466.23	2544392	506190.3	8.7
Hirings (prev 6 months only)	799.4	1169.7	14466.23	2544392	334755.8	12.9
Collective barg job titles	1779.9	2010.5	79078.00	2618743	563196.1	19.9
Less aggregated regions	1476.8	1881.5	59864.77	2544392	534710.6	17.7
Only firms 10+ employees	1123.9	1425.6	12396.18	1892149	382946.4	12.5
Manufacturing sector only	1190.3	1683.6	8653.86	652751	89342.1	13.7

Notes: 'Benchmark' measurement type is the main one adopted in the paper, based on approximately 1,400 occupations and 30 districts. 'Hirings in previous 6 months' is the same approach except that the HHI hirings measure is based on workers hired over the previous six months only (and not the previous 12 months, as in the benchmark and all other measurement approaches). 'Collective bargaining titles' is the same approach as the benchmark model except that, instead of considering occupations, we differentiate occupations by using the collective bargaining job titles (about 30,000). 'Smaller districts' is the same approach as the benchmark model except that, instead of considering the 30 district codes above, we consider instead a finer classification, amounting to 452 different codes. 'Only firms 10+ employees' is the same approach as the benchmark model except that we disregard from the analysis firms that, in each year of the analysis, employ with fewer than 10 employees. 'Manufacturing sector only' is based on manufacturing firms only. HHI and number of cells, workers and hirings are unweighted averages of the weighted HHI yearly data, over the 1991-2013 period. The last column indicates the weighted percentage of cells across all years that have HHI levels above 2,500 (workers HHI except the second row, which denotes new hirings HHI).

Table 4: **Wage results, OLS, 1991-2013**

	(1)	(2)	(3)
Log Herfindhal Index	0.045 (0.000)***	0.018 (0.000)***	0.030 (0.000)***
Constant	8.151 (0.000)***	8.297 (0.000)***	8.232 (0.001)***
<i>N</i>	47612744	47612704	47609180
adj. R^2	0.929	0.959	0.961
F	666,274	39,873	29,708
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
Occupation x District FE	0	0	1
Firm FEs	0	0	0
Worker FEs	0	0	0

Notes: The columns present different specifications of wage equation 2. The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above - see Table 2 - and employment levels. '(Occupation x District) FEs' denote fixed effect for each district-occupation pair. '1' denotes that the set of instruments in the row is included in the specification. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 5: **Wage results, OLS incl worker fixed effects, 1991-2006**

	(1)	(2)	(3)
Log Herfindhal Index	0.012 (0.000)***	0.006 (0.000)***	0.004 (0.000)***
Constant	9.402 (0.000)***	9.434 (0.001)***	9.444 (0.001)***
N	27826468	27826427	27822892
adj. R^2	0.983	0.984	0.984
F	34,853	2,566	556.7
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Worker FEs	1	1	1

Notes: The columns present different specifications of wage equation 2. The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above - see Table 2 - and employment levels. '(Occupation x District) FEs' denote fixed effect for each district-occupation pair. '1' denotes that the set of instruments in the row is included in the specification. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 6: **Wage results, IV incl worker fixed effects, 1991-2006**

	(1)	(2)	(3)
Log Herfindhal Index	0.025 (0.000)***	-0.016 (0.001)***	-0.014 (0.000)***
N	27660321	27660305	27656781
adj. R^2	0.983	0.984	0.984
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Worker FEs	1	1	1

Auxilliary regression (First-stage)

Log inverse of number of firms	0.765 (0.000)***	0.554 (0.001)***	0.647 (0.001)***
adj. R^2	0.818	0.889	0.954
F	13,146,519	714,428	1,514,065
Kleibergen-Paap rk Wald F-stat	13,146,519	714,428	1,514,065
P-value	0	0	0
Shea's R2	.5114	.04622	.134

Notes: The columns in the top panel present different specifications of wage equation 2. The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above - see Table 2 - and employment levels. '(Occupation x District) FEs' denote fixed effect for each district-occupation pair. '1' denotes that the set of instruments in the row is included in the specification. The instrument is the average of the log of the inverse of the number of firms in the same occupation and year but other districts. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 7: **Wage results, IV incl worker fixed effects, new hirings HHI measure, 1991-2006**

	(1)	(2)	(3)
Log Herfindhal Index (new hires measurements)	0.024 (0.000)***	-0.015 (0.001)***	-0.013 (0.000)***
<i>N</i>	27220886	27220855	27217927
adj. R^2	0.983	0.984	0.984
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Firm FEs	0	0	0
Worker FEs	1	1	1
<i>Auxilliary regression (First-stage)</i>			
Log inverse of number of firms	0.788 (0.000)***	0.576 (0.001)***	0.659 (0.001)***
adj. R^2	0.806	0.866	0.926
F	14,935,985	782,894	1,448,282
Kleibergen-Paap rk Wald F-stat	14,935,985	782,894	1,448,282
P-value	0	0	0
Shea's R2	.5243	.04411	.09518

Notes: The columns in the top panel present different specifications of wage equation 2. The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above - see Table 2 - but considering new hirings (12 months) and not employment levels. '(Occupation x District) FEs' denote fixed effect for each district-occupation pair. '1' denotes that the set of instruments in the row is included in the specification. The instrument is the average of the log of the inverse of the number of firms in the same occupation and year but other districts. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 8: **Wage results, IV incl worker fixed effects, subset of high HHI levels, 1991-2006**

	(1)	(2)	(3)
Log Herfindhal Index	0.028 (0.001)***	-0.018 (0.002)***	-0.014 (0.002)***
<i>N</i>	6738689	6738668	6734797
adj. R^2	0.987	0.988	0.988
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Firm FEs	0	0	0
Worker FEs	1	1	1
<i>Auxilliary regression (First-stage)</i>			
Log inverse of number of firms	0.447 (0.000)***	0.275 (0.001)***	0.322 (0.001)***
adj. R^2	0.748	0.813	0.896
F	963,732	132,738	239,992
Kleibergen-Paap rk Wald F-stat	963,732	132,738	239,992
P-value	0	0	0
Shea's R2	.2681	.03519	.07313

Notes: The columns in the top panel present different specifications of wage equation 2. Only observations corresponding to the top 25% HHI (employees) levels. The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above - see Table 2 - and employment levels. '(Occupation x District) FEs' denote fixed effect for each district-occupation pair. '1' denotes that the set of instruments in the row is included in the specification. The instrument is the average of the log of the inverse of the number of firms in the same occupation and year but other districts. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table 9: **Wage results, IV incl worker and firm fixed effects, 1991-2006**

	(1)	(2)	(3)
Log Herfindhal Index	0.011 (0.000)***	-0.033 (0.001)***	-0.028 (0.000)***
<i>N</i>	27571762	27571745	27568221
adj. R^2	0.986	0.986	0.986
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Firm FEs	1	1	1
Worker FEs	1	1	1
<i>Auxilliary regression (First-stage)</i>			
Log inverse of number of firms	0.748 (0.000)***	0.565 (0.001)***	0.642 (0.001)***
adj. R^2	0.857	0.906	0.957
F	12,387,424	766,460	1,443,412
Kleibergen-Paap rk Wald F-stat	12,387,424	766,460	1,443,412
P-value	0	0	0
Shea's R2	.5214	.05328	.1335

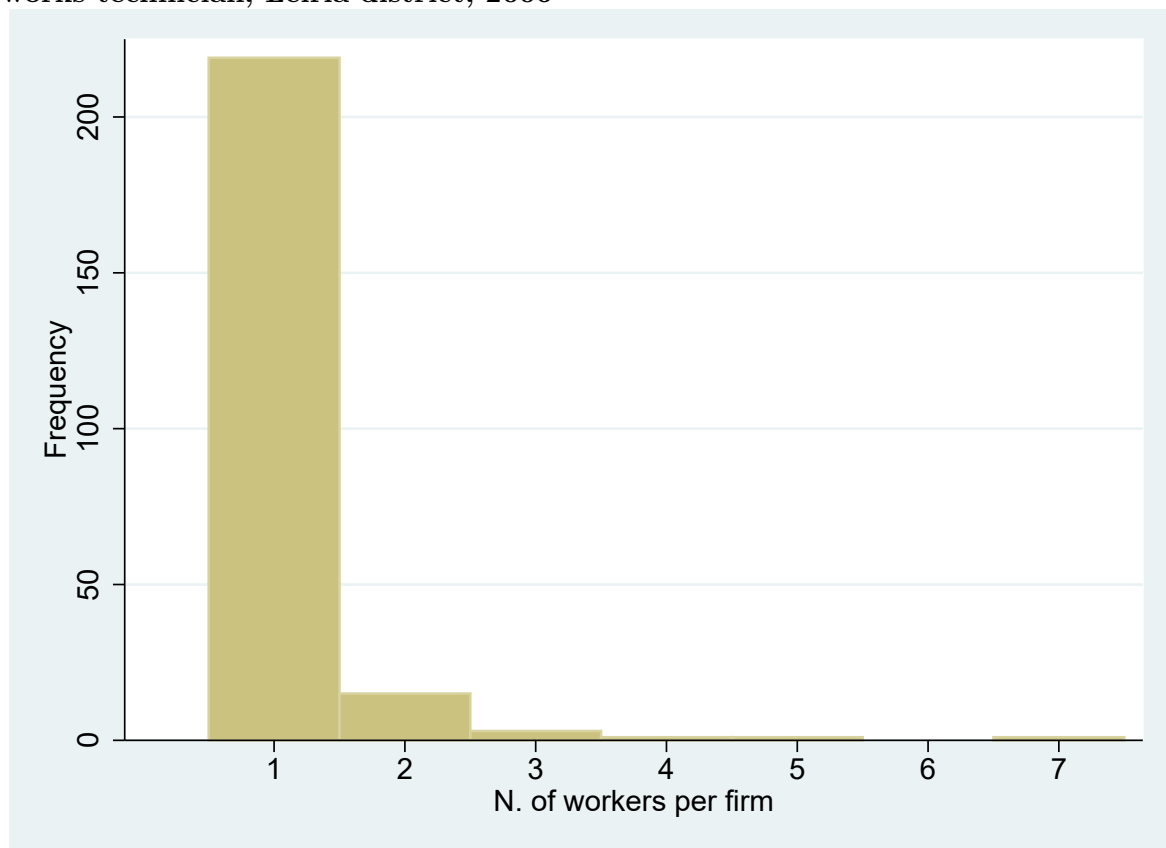
Notes: The columns in the top panel present different specifications of wage equation 2. The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above - see Table 2 - and employment levels. '(Occupation x District) FEs' denote fixed effect for each district-occupation pair. '1' denotes that the set of instruments in the row is included in the specification. The instrument is the average of the log of the inverse of the number of firms in the same occupation and year but other districts. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table A1: **Wage results, OLS, 1991-2006**

	(1)	(2)	(3)
Log Herfindhal Index	0.055 (0.000)***	0.027 (0.000)***	0.034 (0.000)***
Constant	9.160 (0.000)***	9.304 (0.001)***	9.269 (0.001)***
<i>N</i>	29507686	29507644	29504424
adj. R^2	0.937	0.965	0.966
F	659,103	61,548	27,527
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Worker FEs	0	0	0

Notes: The columns present different specifications of wage equation 2. The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above - see Table 2. '(Occupation x District) FEs' denote fixed effect for each district-occupation pair. '1' denotes that the set of instruments in the row is included in the specification. Significance levels: * 0.10, ** 0.05, *** 0.01.

Figure A1: Case study: Distribution of workers per firm, Construction/public works technician, Leiria district, 2006



Notes: Own calculations based on the 'Quadros de Pessoal' data set. Analysis of a particular occupation (Construction and public works technician, code 31120) in a particular district (Leiria) in a particular year (2006). Each observation in the histogram corresponds to one of 240 firms located in the district that employ at least one worker with this occupation in that year. The Herfindhal index (which ranges between 0 and 10,000) for this local labour market in this year is 52.7.

Table A2: **Wage results, IV, 1991-2006**

	(1)	(2)	(3)
Log Herfindhal Index	0.109 (0.000)***	0.137 (0.001)***	0.083 (0.000)***
<i>N</i>	47443125	47443118	47439617
adj. R^2	0.927	0.957	0.960
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Worker FEs	0	0	0
<i>Auxilliary regression (First-stage)</i>			
Log inverse of number of firms	0.746 (0.000)***	0.466 (0.001)***	0.672 (0.000)***
adj. R^2	0.450	0.779	0.951
F	40,718,074	589,771	2,503,240
Kleibergen-Paap rk Wald F-stat	40,718,074	589,771	2,503,240
P-value	0	0	0
Shea's R2	.4446	.01862	.146

Notes: The columns in the top panel present different specifications of wage equation 2. The dependent variable is the log of individual total wage. The Herfindhal index corresponds to the benchmark model presented above - see Table 2 - and employment levels. '(Occupation x District) FEs' denote fixed effect for each district-occupation pair. '1' denotes that the set of instruments in the row is included in the specification. The instrument is the average of the log of the inverse of the number of firms in the same occupation and year but other districts. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table A3: **Wage results, IV incl worker fixed effects, base wages, 1991-2006**

	(1)	(2)	(3)
Log Herfindhal Index	0.019 (0.000)***	-0.031 (0.000)***	-0.028 (0.000)***
<i>N</i>	27658847	27658831	27655306
adj. R^2	0.987	0.988	0.988
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Firm FEs	0	0	0
Worker FEs	1	1	1
<i>Auxilliary regression (First-stage)</i>			
Log inverse of number of firms	0.765 (0.000)***	0.554 (0.001)***	0.647 (0.001)***
adj. R^2	0.818	0.889	0.954
p-value	0	0	0
Kleibergen-Paap rk Wald F-stat	13,144,409	714,388	1,513,979
P-value	0	0	0
Shea's R2	.5114	.04622	.134

Notes: The columns in the top panel present different specifications of wage equation 2. The dependent variable is the log of individual base wage (not total wage as before). The Herfindhal index corresponds to the benchmark model presented above - see Table 2 - and employment levels. '(Occupation x District) FEs' denote fixed effect for each district-occupation pair. '1' denotes that the set of instruments in the row is included in the specification. The instrument is the average of the log of the inverse of the number of firms in the same occupation and year but other districts. Significance levels: * 0.10, ** 0.05, *** 0.01.

Table A4: **Wage results, IV incl worker fixed effects, collective bargaining job titles, 1991-2006**

	(1)	(2)	(3)
Log Herfindhal Index	0.025 (0.000)***	-0.022 (0.001)***	-0.015 (0.001)***
<i>N</i>	27660321	27660294	27654671
adj. R^2	0.983	0.984	0.984
Year FEs	1	1	1
Occupation FEs	0	1	0
District FEs	0	1	0
(Occupation x District) FEs	0	0	1
Firm FEs	0	0	0
Worker FEs	1	1	1
<i>Auxilliary regression (First-stage)</i>			
Log inverse of number of firms	0.765 (0.000)***	0.352 (0.001)***	0.498 (0.001)***
adj. R^2	0.818	0.894	0.964
F	13,146,519	183,854	627,515
Kleibergen-Paap rk Wald F-stat	13,146,519	183,854	627,515
P-value	0	0	0
Shea's R2	.5114	.01233	.0658

Notes: The columns in the top panel present different specifications of wage equation 2. The dependent variable is the log of individual total wage. The Herfindhal index corresponds to collective bargaining job titles and employment levels. '(Occupation x District) FEs' denote fixed effect for each district-occupation pair. '1' denotes that the set of instruments in the row is included in the specification. The instrument is the average of the log of the inverse of the number of firms in the same occupation and year but other districts. Significance levels: * 0.10, ** 0.05, *** 0.01.